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# Wearable devices for anxiety & depression: A scoping review

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ABSTRACT

*Background:* The rates of mental health disorders such as anxiety and depression are at an all-time high especially since the onset of COVID-19, and the need for readily available digital health care solutions has never been greater. Wearable devices have increasingly incorporated sensors that were previously reserved for hospital settings. The availability of wearable device features that address anxiety and depression is still in its infancy, but consumers will soon have the potential to self-monitor moods and behaviors using everyday commercially-available devices.
*Objective:* This study aims to explore the features of wearable devices that can be used for monitoring anxiety and depression.
*Methods:* Six bibliographic databases, including MEDLINE, EMBASE, PsycINFO, IEEE Xplore, ACM Digital Library, and Google Scholar were used as search engines for this review. Two independent reviewers performed study selection and data extraction, while two other reviewers justified the cross-checking of extracted data. A narrative approach for synthesizing the data was utilized.
*Results:* From 2408 initial results, 58 studies were assessed and highlighted according to our inclusion criteria. Wrist-worn devices were identified in the bulk of our studies ($n$ = 42 or 71%). For the identification of anxiety and depression, we reported 26 methods for assessing mood, with the State-Trait Anxiety Inventory being the joint most common along with the Diagnostic and Statistical Manual of Mental Disorders ($n$ = 8 or 14%). Finally, $n$ = 26 or 46% of studies highlighted the smartphone as a wearable device host device.
*Conclusion:* The emergence of affordable, consumer-grade biosensors offers the potential for new approaches to support mental health therapies for illnesses such as anxiety and depression. We believe that purposefully-designed wearable devices that combine the expertise of technologists and clinical experts can play a key role in self-care monitoring and diagnosis.

## 1. Introduction

### 1.1. Background

Globally, "common mental illnesses" such as anxiety and depression are widespread. The lifetime prevalence of depression varies by culture and is as much as 20% in countries such as the United States [1,2]. Not only do depression and anxiety have a significant economic impact on society [3], but they also significantly impact individuals in terms of lost years due to ill health. Disability-adjusted life years for mental illness are comparable to those for cardiovascular and circulatory illnesses. The proportion of Years Lived with Disability for mental health problems is significant, at 32.4% globally [4]. Not only is depression a major risk factor for suicide [5], those affected tend to have a shorter lifespan due to health issues correlated to their mental status [6]. The global figures for anxiety are also unfavorable, with 3.76% of the world population reported to have suffered from an anxiety disorder; the figures have remained unchanged since 1990 [7].

Recent studies have looked at self-care mobile applications (apps) [8], considered a vital tool for giving patients the feeling of autonomy

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for self-regulating their health needs. However, few reviews exist on the technical solutions linked to mobile apps. In this study, we focus on a large class of such solutions, namely on publicly available wearable devices and their tools to monitor, detect, diagnose, or manage mental health [9]. Wearable devices, such as smart watches and wrist bands, have given rise to wearable devices becoming influential technologies. They affect our decisions and behaviors in much the same way that mobile apps have in the domain of mental health [10], albeit in comparison, wearable devices are still in their infancy. Integrating sensors into wearable devices has enhanced their monitoring capabilities to a level that was previously reserved to hospital settings. While wearable device technologies have long been used in health interventions in clinical settings with promising results [11], the ease and accessibility of consumer-level devices containing such integrated sensors, be it in clothes or other accessories, could further democratize their use and might provide health benefits to users suffering from anxiety and depression. At the same time, that democratization is raising questions about the appropriate limits of data use in the provision of care through wearables [12].

### 1.2. Research problem and aim

With a growing emphasis on alleviating the onerous symptoms of mental health disorders—particularly those that have been exacerbated by the global response to COVID-19—the necessity for a review that can enlighten individuals looking for easily available mental health-focused wearable devices has never been greater. As this field is fast evolving, wearable devices require the same quality reviews previously published on app features [13], both to enable consumers to make informed decisions and the research community to identify gaps and opportunities. The authors aim to explore features of publicly available WD technologies within the domain of anxiety and depression. Many studies have been conducted about WDs but to the best of our knowledge this is the first scoping review (overview of the available research evidence) looking at WDs and their use with anxiety and depression. We hope to provide researchers with some extra insight of this emerging field. Our review assesses information and could form a pre-cursor for a future systematic review.

## 2. Methods

This scoping review was carried out to satisfy the study's goals of exploring features of wearable devices for anxiety and depression. The PRISMA Extension for Scoping Reviews (PRISMA-ScR) [14] was utilized as a guiding approach to construct a complete scoping review.

### 2.1. Search strategy

#### 2.1.1. Search sources

Searches for this study were executed in the following bibliographic databases: MEDLINE, EMBASE, PsycINFO, IEEE Xplore, ACM Digital Library, and Google Scholar.

Bibliographic collection took place from July 10th to July 12th, 2021. Because Google Scholar typically returns several hundred items sorted by relevance to the search topic, only the first 100 hits were scanned. The reference lists of the included studies and reviews were also screened to look for other publications relevant to the review. Additionally, relevant papers that cited the included studies were located by using Google Scholar's "cited by" tool (forward reference list checking).

#### 2.1.2. Search terms

For the present study, two sets of keywords were designed to search databases. We considered the subject terms included in the databases to complete our search queries. We combined four keywords describing the relevant population (anxiety, depression, depressed, and anxious) with each relevant intervention (wearable*, smart*). For example, the following search term was applied in Google Scholar: ("Wearable*" OR "smart*" OR "Wearable device*") AND ("anxiety*" OR "depression" OR "depressive*" OR "depression*" OR "anxious*").

### 2.2. Study eligibility criteria

Studies were chosen based on the criteria in Table 1. Only peer-reviewed articles, conference proceedings (not abstracts), and reports were considered. In addition, only studies published in English and during the last ten years were included in this study. Dissertations, theses, conference abstracts (not proceedings), proposals, and editorials were not accepted.

Only studies that addressed publicly available wearable devices used for anxiety and depression purposes that did not require a hospital setting were included.

### 2.3. Study selection

The studies for this review were chosen in two stages. Two reviewers independently reviewed the titles and abstracts of all retrieved papers in the first stage. In the second phase, the same reviewers read the complete texts of the papers included in the first step separately. If there were any disputes between the two reviewers, these were settled by consulting a third reviewer, both during the first and second steps of the selection process.

### 2.4. Data extraction and data synthesis

The included studies were screened in two phases by four reviewers. As indicated in Multi-media Appendix B, two reviewers created the data extraction form. Two additional reviewers independently undertook the data extraction procedure, and any differences were addressed by the third reviewer. The first reviewers synthesized relevant extracted study data from the Microsoft Excel data extraction sheet. To synthesize the collected data from the included research, the narrative technique was used. Narrative research is a broad term encompassing a variety of approaches that rely on people's written or spoken words, as well as their visual representations [14].

## 3. Results

### 3.1. Search results

The search of six bibliographic databases yielded 2408 citations. As shown in Fig. 1, 598 duplicates were excluded, leaving 1810 unique titles and abstracts. Of those, 1461 citations were further excluded after screening their titles and abstracts. Of the remaining 349 references, 303 publications were excluded during the full text screening. Finally, 46 unique individual studies were identified. Backward reference list

**Table 1**
Inclusion and exclusion criteria.

| Criteria | Specified criteria |
|---|---|
| Inclusion | • Any wearable technology or approaches used for anxiety and depression for any purpose such as: screening, diagnosis, treatment, monitoring, tracking, etc.<br>• Publicly available, consumer-grade devices (e.g., wrist band, glasses, clothes etc.)<br>• Studies published between 2010 and 2021<br>• Peer-reviewed articles, theses, conference proceedings, and reports<br>• English articles |
| Exclusion | • Proposed new devices not currently on the market<br>• Sensors or tracking devices infused inside a person's body<br>• Wearable devices that need professional or hospital settings<br>• Reviews, conference abstracts, dissertations, proposals, editorials, commentaries |

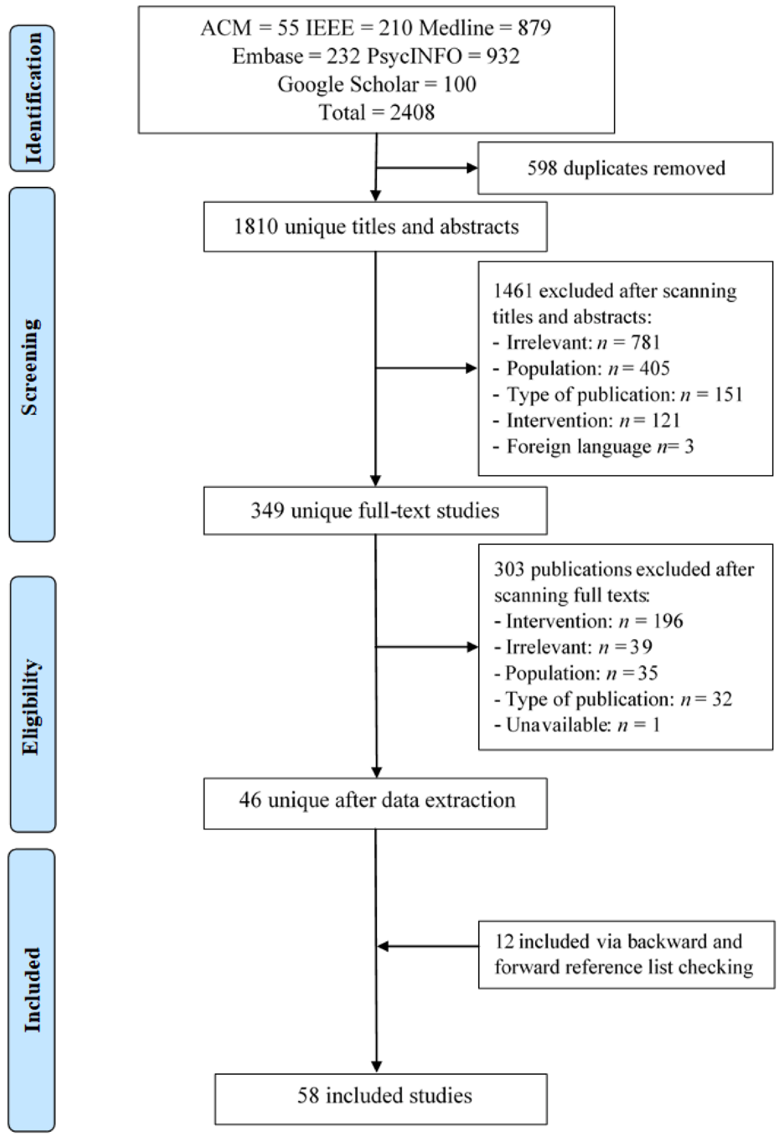


**Fig. 1.** Flowchart of the study selection process.

checking and forward reference list checking yielded 12 new studies. The synthesis includes a total of 58 articles.

### *3.2. General description of included studies*

As presented in Table 2, most published studies were journal articles (71%), and less than one-third were conference articles (29%). Although studies were published in more than 17 countries, about 23.7% of the included studies were published in the USA. More than half of the studies were published between 2016 and 2021 (51%).

### *3.3. Features of wearable devices*

A smart band was utilized in 32% of the studies, and a smartwatch in 29% of the studies. The actigraphy brand is the most commonly available commercial brand used by 15% of the studies. Only 7% of the studies utilized smart glasses. Smart belts, smart necklaces, and smart clips were only used by 3% of the studies. Other uncommon devices were described only once, such as a smart ring, human performance electrodes device, skin conductance biofeedback device, and a wearable near-infrared spectroscopy (NIRS).

The included studies show a clear dominance of wrist-worn devices (71%) over devices worn across the rest of the body or attire: waist ($n$ = 5), head ($n$ = 5), chest ($n$ = 2), suit ($n$ = 2), neck ($n$ = 2), finger ($n$ = 2), or elsewhere ($n$ = 2) together make up the remaining 20%. Note that numbers do not add up since four references (S1, S9, S26, S29) describe the use of multiple devices.

Table 2 also presents the 26-moods assessment methods discussed by included studies for identification of anxiety and depression. The most common methods were State-Trait Anxiety Inventory (14%) and Diagnostic and Statistical Manual of Mental Disorders (14%). The mental health illness most targeted by wearable devices in the included studies is depression (47%), whereas anxiety was only assessed in 25% of studies. More than a quarter (27%) of the included studies assessed both mental illnesses.

### *3.4. Technical device operation details and evaluation*

Among the 58 studies, Table 3 highlights that Fitbit (16%) is the most common wearable device technology brand producer, followed by Actiwatch and Empatica (12%). Five different host devices were identified that were used as a gateway for collected data storage or further processing. Amongst them, smartphones (45%) are the most frequent devices, followed by computers (10%), and online websites (3%),

**Table 2**
General characteristics of included studies.

| Characteristics | Number of studies | Studies (see Appendix A) |
|---|---|---|
| Year of publication | 2021: 9 | S14, S15, S30, S32, S36, S39, S42, S45, S47 |
| | 2020: 9 | S12, S19, S25, S26, S29, S34, S38, S49, S57 |
| | 2019: 8 | S1, S11, S17, S21, S41, S43, S48, S58 |
| | 2018: 8 | S8, S24, S28, S31, S37, S40, S52, S54 |
| | 2017: 11 | S2, S4, S6, S9, S10, S22, S35, S50, S51, S55, S56 |
| | 2016: 4 | S16, S18, S23, S46 |
| | 2015: 5 | S3, S5, S27, S44, S53 |
| | 2014: 1 | S7 |
| | 2012: 1 | S20 |
| | 2011: 1 | S33 |
| | 2010: 1 | S13 |
| Country | USA: 24 | S1, S3, S9, S13, S14, S18, S22, S26, S27, S28, S29, S31, S32, S34, S35, S36, S37, S40, S41, S47, S48, S50, S52, S54 |
| | UK: 6 | S2, S10, S42, S43, S51, S58 |
| | Germany: 4 | S15, S16, S23, S45 |
| | Japan: 4 | S6, S25, S38, S53 |
| | Canada:2 | S4, S24 |
| | China: 3 | S12, S55, S56 |
| | Australia:2 | S11, S57 |
| | Korea: 2 | S17, S49 |
| | Austria: 2 | S7, S8, |
| | Ireland: 2 | S30, S46 |
| | Brazil: 1 | S19 |
| | Finland: 1 | S39 |
| | Norway:1 | S5 |
| | Italy:1 | S21 |
| | Netherland: 1 | S44 |
| | Switzerland: 1 | S33 |
| | Mexico: 1 | S20 |
| Type of publication | Journal article: 41 | S1, S2, S4, S5, S6, S7, S8, S9, S11, S12, S13, S14, S15, S17, S18, S19, S20, S21, S24, S25, S26, S27, S28, S29, S30, S32, S33, S34, S36, S39, S41, S42, S43, S44, S45, S46, S49, S51, S54, S57, S58 |
| | Conference:17 | S3, S10, S16, S22, S23, S31, S35, S37, S38, S40, S47, S48, S50, S52, S53, S55, S56 |
| Wearable Device Type | Smart band: 19 | S2, S11, S18, S19, S25, S26, S27, S28, S31, S34, S35, S38, S42, S43, S48, S50, S51, S52, S57 |
| | Smart watch: 17 | S4, S8, S12, S15, S16, S17, S22, S23, S26, S30, S32, S36, S37, S49, S55, S56, S58 |
| | Actigraphy: 8 | S5, S6, S7, S9, S13, S20, S33, S44 |
| | Smart glass: 4 | S8, S9, S21, S45 |
| | Smart Belt:3 | S40, S41, S54 |
| | Smart shirt:2 | S1, S10 |
| | Smart necklace: 2 | S14, S47 |
| | smart clip: 2 | S24, S29 |
| | Smart Ring: 1 | S39 |
| | Human Performance electrodes Device: 1 | S3 |
| | Skin conductance biofeedback device:1 | S46 |
| | Wearable near-infrared spectroscopy (NIRS): 1 | S53 |
| Placement of wearable device | Wrist: 42 | S1, S2, S4, S5, S7, S9, S11, S12, S13, S15, S16, S17, S18, S19, S20, S22, S23, S25, S26, S27, S28, S30, S31, S32, S33, S34, S35, S36, S37, S38, S42, S43, S44, S48, S49, S50, S51, S52, S55, S56, S57, S58 |
| | Waist: 5 | S6, S28, S40, S41, S54 |
| | Head: 5 | S8, S9, S21, S45, S53 |
| | Chest:2 | S3, S26 |
| | Suit: 2 | S1, S10 |
| | Neck: 2 | S14, S47 |
| | Finger: 2 | S39, S46 |
| | Anywhere: 2 | S24, S29 |
| Mood assessed methods | State-Trait Anxiety Inventory: 8 | S12, S21, S23, S26, S48, S51, S55, S56 |
| | Diagnostic and Statistical Manual of Mental Disorders (DSM): 8 | S3, S7, S8, S20, S32, S40, S41, S54 |
| | Hamilton Depression Rating Scale (HAM-D): 6 | S6, S7, S9, S25, S33, S34 |
| | Patient Health Questionnaire (PHQ): 6 | S30, S36, S42, S49, S52, S58 |
| | Online interview or survey: 5 | S1, S11, S15, S24, S27 |
| | Montgomery-Asberg depression rating scale (MADRS): 4 | |
| | Depression, Anxiety and Stress Scale (DASS):3 | S20, S25, S44, S57 |
| | NA: 3 | S16, S18, S39 |
| | Ecological Momentary Assessment (EMA): 2 | S10, S22, S47 |
| | Gamification: 2 | S17, S49 |
| | Profile of Mood States (POMS): 2 | S19, S46 |
| | Generalised Anxiety Disorder questionnaire (GAD): 2 | S28, S53 |
| | Beck's Depression Inventory (BDI): 2 | S30, S43 |
| | Center for Epidemiologic Studies Depression scale (CES-D): 1 | S4, S21, |
| | Depression and Anxiety Mood Scale (DAMS): 1 | S14 |
| | Activities of daily living (ADL): 1 | S38 |
| | Clinical Global Impression (CGI): 1 | S2 |
| | Heart Rate Variability (HRV): 1 | S57 |
| | Mood & Anxiety Symptoms Questionnaire (MASQ): 1 | S50 |
| | Positive and Negative Syndrome Scale (PANSS): 1 | S29 |
| | Positive and Negative Affect Schedule (PANAS): 1 | S5 |
| | moderate-to-vigorous physical activity (MVPA):1 | S35 |
| | Quick Inventory of Depressive Symptomatology (QIDS): 1 | S28 |
| | Social Interaction Anxiety Scale (SIAS):1 | S31 |
| | Symptomatic Organic Mental Disorder Assessment Scale (SOMAS):1 | S37 |
| | The UWIST Mood Adjective Checklist: 1 | S5<br>S46 |
| Mental disorder | Depression: 27 | S2, S4, S5, S6, S7, S8, S9, S13, S14, S17, S20, S24, S25, S30, S31, S32, S33, S34, S35, S36, S42, S44, S49, S52, S53, S57, S58 |
| | Anxiety: 15 | S1, S10, S11, S15, S22, S23, S26, S37, S45, S46, S47, S48, S51, S55, S56 |
| | Depression & Anxiety: 16 | S3, S12, S16, S18, S19, S21, S27, S28, S29, S38, S39, S40, S41, S43, S50, S54 |

**Table 3**
Technical device operation details.

| Characteristics | Number of studies | Study ID |
|---|---|---|
| Device Technology brands | Fitbit: 9 | S1,S4,S11,S24,S27,S31, S38,S42,S43 |
| | ActiWatch: 7 | S5,S7,S13,S15,S17,S20, S33 |
| | Empatica: 7 | S18,S26,S34,S35,S47,S48, S50 |
| | Apple watch:3 | S11,S30,S58 |
| | Proposed watches using ARM Cortex:3 | S12,S22,S23 |
| | Acti Graph:2 | S28,S32 |
| | 3-space sensor:2 | S40,S41 |
| | Estera Corporation:1 | S6 |
| | Microsoft band:2 | S37,S52 |
| | *Re*-Timer and Actiware:2 | S8,S9 |
| | Others:22 | S3, S6,S14,S16,S19,S21, S25,S29, S36,S39,S44,S45,S46,S49, S51,S53-S55,S57 |
| | N/A:3 | S2,S10,S56 |
| Host device | Smartphone: 26 | S1,S3,S11,S16,S19,S21, S25-S31,S34-S39,S43,S45, S46,S49,S51,S52,S56,S58 |
| | Computer: 6 | S7,S12,S13,S23,S33,S47 |
| | Online database: 2 | S4, S24 |
| | Stored locally in the flash memory: 1 | S50 |
| | N/A: 20 | S2,S5-S6,S8-S10,S14,S15, S17,S20,S22,S32,S40-S42, S44,S48,S53-S55,S57 |
| Operating systems compatible with | Android: 3 | S35, S36, S44 |
| | iOS: 3 | S31,S40,S59 |
| | Android and iOS: 10 | S3,S16,S19,S27,S31,S36, S52,S49, S55,S56 |
| | N/A: 42 | S2,S4-S15,S17,S18,S20-S26,S28, S29,S32,S33,S37, S38,S40,S41,S42, S44-S48,S50,S51,S53,S54,S57 |
| Mode of Data transfer | Bluetooth: 14 | S3,S18,S19,S23,S25,S27, S28,S36, S43,S46,S47, S49,S51,S52 |
| | Internet (WiFi, Mobile data; optionally combined with cloud storage): 11 | S4,S16,S24,S31,S34,S35, S37,S39, S45,S47,S58 |
| | Removable media: 5 | S7,S10,S13,S26,S33 |
| | Wired:1 | S53 |
| | N/A: 27 | S1,S2,S5,S6,S8,S9,S11, S12,S14, S15,S17,S20,S21, S29,S30,S32,S38,S40-S42, S44,S48,S50,S54,S55-S57 |
| Effectiveness measure | Statistical methods/ measures: 40 | S1,S2,S4,S5,S10,S12,S13, S14,S17,S18, S20,S21,S23, S25,S26,S28,S29,S32-S36, S38,S40-S42,S44-S46,S48, S49,S51,S52,S54-S58 |
| | Pre-post testing: 2 | S6,S53 |
| | User Interviews:1 | S16 |
| | Technology Acceptance Model: 1 | S19 |
| | N/A: 14 | S3,S8,S9,S11,S15,S22, S24,S27,S30, S37,S39,S43, S47,S50 |
| Number of Participants | 0–49: 29 | S3,S4,S6,S7-S10,S14,S16-S20,S24,S27,S28,S35-S37, S44,S45,S48-S51,S53,S56-S58 |
| | 50–99:20 | S5,S12,S13,S21-S23,S25, S26,S30,S32-S34,S38-S41, S46,S52,S54,S55 |
| | 100–300:6 | S1,S2,S11,S15,S29,S31 |
| | above 300:2 | S42,S43 |
| | closed laboratory setting:1 | S47 |
| Study experimentation duration | <=1 day: 4 | S5,S33,S46,S51 |
| | <=1 week:8 | S2,S25,S31-S32,S44,S52, S53,S57 |
| | <=1 month:15 | S3,S6,S7,S13,S17,S19, S27-S29,S36-S39,S49,S50 |
| | <=1 year:15 | S1,S4,S8,S9,S11,S14,S18, S20,S24, S30,S34,S35,S41, S54,S58 |
| | Above 1 year:3 | S15,S42,S43 |
| | N/A:13 | S10,S12,S16,S21-S23,S26, S40,S45,S47,S48,S55,S56 |

whereas 34% did not use any host terminal. The most used operating systems in wearable devices are Android (5%) and iOS (5%). Other studies supported both of these OSes (17%), though the majority of studies (72%) did not specify the compatible operating system, leading us to speculate that they may be compatible with both systems, as Android and iOS together represent more than 99% market share as of this writing [15]. The most prevalent data transfer mode between wearable and host devices was Bluetooth (22%), followed by internet technology (19%) in the form of WiFi or cellular data. Few devices made use of removable media (9%) such as memory cards, whereas a single ($n = 1$) study used wired connections.

Studies performed experiments on these wearable devices using small sets of participants mostly below age 50 (50%) and were carried out for months (26%).

Various methods were used to measure the effectiveness of wearable devices for assessments of anxiety and depression. Among those, statistical methods (69%) were most used. Such methods mainly constitute tests such as Pearson's and Spearman correlation coefficient, p-value, F1 score, accuracy, and the ANOVA test, along with many others. Pre-/post testing (3%), user interviews and a Technology Acceptance Model were also used by single studies.

## 4. Discussion

### 4.1. Principal findings

Considering that the Fitbit (released in 2009) and the Apple Watch (released in 2015) were seminal products that paved the way for early wearable devices, it is hardly surprising that most of the devices used by the studies are wrist-worn. We believe that their resemblance to wrist watches lends legibility to such devices and allows users to check them frequently and discretely. Furthermore, most of the recent studies (e.g., 5 years) report the use of connected devices, for example connected via WiFi or Bluetooth to a host smartphone. Among the many likely reasons for this trend are (a) a decline in price for mobile online data, (b) ever more energy-efficient local connectivity technology, such as Bluetooth Low Energy, (c) the opportunity to "outsource" more complex tasks to considerably more powerful host devices, thereby extending battery life on the wearable device, (d) the convenience of being able to explore one's data on bigger screens or across device boundaries ("cloud storage"), and (e) the pervasiveness of mobile devices. However, whereas a modern lifestyle seems to drive the development of technology that supports personal fitness (e.g., Fitbit and the many apps that track one's personal fitness status, including vitals such as heart rate or body temperature), most devices used in studies are purpose-shifted, that is, they are used outside of their original purpose for the benefit of mental health applications. We believe that the effectiveness of such purpose-shifted devices deserves more scrutiny, possibly in the form of a separate, systematic review, although another possible explanation is that regular exercise may be associated with some improvement in mental well-being. [16,17].

We see the main potential of wearable devices being their ability to track or infer habits, such as work-rest balances and exercise levels, from various biosensors, potentially allowing medical experts (or software expert systems) to infer the user's mood or therapeutical progress. It is particularly useful that relevant data can be gathered from more data points during the day than with traditional hospital visits. This may, soon, prove itself to be the enabling technology behind mental health-targeting software becoming increasingly augmented by additional biosensors. Consequently, purposefully wearable devices that target mental health issues designed in collaboration between technologists and clinical experts could add substantial (self-)diagnostic and therapeutic value.

However, we must note that most of the studies are either woefully short ($n = 27$, less than a month) or underpopulated ($n = 29$, less than 50 participants). Only two of the studies (S42, S43) recruited a population of over 300 participants and lasted more than a year. In the context of mental health disorders, it is important to note that improvement often comes gradually and requires expert intervention for several months (e.g., cognitive behavioral therapy (CBT) to treat anxiety typically involves a meeting with a therapist for 1 h per week for 3—4 months, according to the UK's National Health Service [18]. Further, for some mental health disorders, the positive effects of CBT may require years of follow-up treatment to be maintained [19].

### 4.2. Strengths

The review has been reported according to the PRISMA Extension for Scoping Reviews; therefore, it can be considered a review of good quality. Furthermore, this study is the first review in the literature that has focused on wearable devices targeting anxiety and depression. Thus, this study could assist readers with making decisions about the best wearable devices to use in the current market, and could highlight gaps to the research community and to technology hardware and software developers (e.g., the need for larger and longer systematic studies).

The most popular databases in both the healthcare and information technology fields were searched to retrieve as many relevant studies as possible. The authors searched Google Scholar and conducted backward and forward reference list checking to identify gray literature, reducing the risk of publication bias. All studies included in this review were from peer-reviewed journals.

### 4.3. Limitations

Some limitations are that only English studies were included, and that only studies published between 2010 and 2021 were included, by the time the study had gone through the review process and published no doubt in this fast paced and rapidly changing field it is not farfetched to expect yearly updates for this review. Due to practical restrictions (e.g., accessing Web of Science and Scopus), we may have overlooked some pertinent research papers. In addition, the databases were searched using only the terms "wearable*, smart*" for this study. We only included studies that utilized commercial wearable devices that require no clinical setting. Therefore, other kinds of wearable devices, such as EEG and ECG, were excluded. Finally, this is a scoping review that does not critically assess the quality of the included studies. Although the different wearable device technologies were examined, the review falls short of reporting the effectiveness measure values, and therefore does not assess performance. The latter goes beyond the scope of a scoping review and would be more suited to a full systematic review article. We hope a systematic review shall follow.

### 4.4. Practical and research implications

The emergence of wearable devices and their integration with smart devices such as mobile phones, paired with the ease and style in which wearable devices can be worn in the form of wrist bands and watches, highlights that wearable devices have gained wide acceptance. What makes them appealing to mental health applications is that they can be equipped with a multitude of biosensors that measure vitals and biosignals casually and at the user's leisure. As a result, it has never been easier to gather data on patients' habits, moods, etc. Given today's increasing popularity of purpose shifted wearable devices to counteract anxiety and depression (e.g., exercise trackers), it is likely that a boom of purposefully designed wearable devices in mental health is imminent. This assessment is supported by the acceptance and success of wearable devices in general health care in the last decade (e.g., heart rate monitors, body temperature scanners, respiratory monitors, blood sugar monitors, etc.). Especially in the domain of self-care, wearable devices paired with smart devices could allow users access to early-onset diagnostic tools to monitor habits and mood, recommend unsupervised therapy, or instigate referrals to therapeutic experts. This review outlined the significance of such devices in anxiety and depression. Just as mobile apps for mental health have become more prominent in the past decade, purpose shifted wearable devices can be predicted to make tremendous leaps in the coming years. In particular, the setting of wearable devices in an Internet-of-Things (IoT) environment seems to open limitless possibilities, combining data gathered from wearable device sensors with other patient and personal data in real-time.

However, every new technology must undergo careful evaluation and scrutiny. Rigorous, systematic studies involving larger populations over longer time periods are direly needed. A future review should be conducted to include device and the parameters for judging accuracy, not only from the viewpoint of professional experts, but also that of those who agree to be assessed, including those who may be mildly affected, but also those with severe mental illness. Other research directions include general questions of privacy and data sovereignty that arise from the use of cloud-based storage of data or in the context of myriads of interconnected devices which are also connected to the datacenters of hospitals, private companies, and governments. There are related questions concerning the scope of an individual's consent to use their data, and potential liability where data is misused. Not only is the method of obtaining proper informed consent important, but also whether consent should be obtained at multiple stages of a study. That consent process may also be multi-layered, involving several entities. On liability, there are risks with misdiagnoses, harmful recommendations, or recommendations that do not adhere to the requisite standard of care.

These questions are becoming ever more pertinent with the integration of artificial intelligence into wearable technologies. The potential legal implications are significant, with vast data now being incorporated into making wearable devices viable diagnostic and monitoring tools on a larger scale. Unintended consequences may arise from data security breaches or the reidentification of previously de-identified data.

Further, the status of wearables as being either 'medical' or 'therapeutic' and their risk classification will have implications for their permitted use and how the associated mental health data should be managed. Ultimately, there will be questions about the appropriate balance between allowing the necessary flow of information to ensure that the devices are useful, and the flow of data that goes beyond what is needed. The most rewarding and exciting research will require a multidisciplinary endeavor of engineers, medical practitioners, policy makers and legal experts.

## 5. Conclusion

This is the first review scoping the landscape of using wearable devices as ingredients to alleviate mental health symptoms, in particular: anxiety and depression. Despite most wearable devices being purpose-shifted from fitness monitoring or other smart functions, the emergence of affordable, consumer-grade biosensors offers the potential for new approaches to support mental health therapies. Their main potential is their ability to track users' habits and vitals at many measurement points at the leisure of the user. Such data could either fuel software expert systems, supporting early (self-)diagnosis or supporting full, expert-guided treatment. Two main research directions as of this writing are: (a) a focus on purposefully designed wearable devices that combine the expertise of technologists and clinical experts and (b) longer and better populated systematic studies scrutinizing the benefits of wearable devices, both as data gathering and recommendation devices in the context of anxiety and depression.

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## Contributor ship

Mahmood and Sarah performed the searches, Hashem and Sara performed the data extraction. Arfan drafted the initial manuscript, Alaa and Mowafa guided and supervised the process. All other authors contributed to the final manuscript write up.

## Declaration of Competing Interests

The authors have no competing interests to declare.

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## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.cmpbup.2023.100095.

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